

Claremont Colleges Scholarship @ Claremont

CMC Senior Theses

CMC Student Scholarship

2019

Deal Or No Deal: The Relationship Between Firm Determinants & Venture-Capital Financing Decisions

Raghav Prasad

Recommended Citation

Prasad, Raghav, "Deal Or No Deal: The Relationship Between Firm Determinants & Venture-Capital Financing Decisions" (2019). *CMC Senior Theses*. 2233.
https://scholarship.claremont.edu/cmc_theses/2233

This Open Access Senior Thesis is brought to you by Scholarship@Claremont. It has been accepted for inclusion in this collection by an authorized administrator. For more information, please contact scholarship@cuc.claremont.edu.

Claremont McKenna College

Deal Or No Deal: The Relationship Between Firm Determinants &
Venture-Capital Financing Decisions

submitted to

Professor Janet K. Smith

by

Raghav Prasad

for

Senior Thesis

Spring 2019

04/29/2019

ACKNOWLEDGEMENTS

I would like to extend my gratitude to Professor Janet K. Smith for her continued support and guidance that made this paper possible. Thank you for being so approachable, flexible and insightful during this entire process. I would also like to thank my professors here at CMC for always encouraging me to challenge myself and be the best version of myself. Additionally, I am grateful to my friends who have been a source of tremendous support over the past four years. The amazing memories I have shared with all of you will remain with me forever. Additionally, I want to thank my family for always believing in me and making this phenomenal education possible. Thank you all for the support, encouragement and laughs.

ABSTRACT

In this paper, I analyze how firm attributes such as their age, industry, nature of industry, spinoff status and debt ratio influence venture-capital financing decision. I look at a sample of 280 firms that went public in the United States between 2015- 2019. This paper finds that firm age and debt are negatively related to the likelihood of being venture-capital backed. It also finds that firms in technology and biotechnology industries are more likely to be backed by a venture-capitalist.

In memory of Sarla Prasad

1) Introduction

The sky-high valuations and initial public offerings of venture-capital backed firms have been making headlines. Venture-backed firms such as Uber, Airbnb, Slack and Palantir are likely to go public this year. In fact, levels of VC investment in the U.S economy have remained strong with \$32.6 billion invested during Q1 of 2019 and are expected to continue this way due to the scheduled IPO's of unicorns later in the year (Settles, 2019). The We Company and Flexport closed the largest deals in terms of investment size in Q1 of 2019 (Settles, 2019). Last year, the highest number of VC-backed firms went public, breaking the record of 2014 (Rooney, 2019). Furthermore, the spend on private companies by VC's hit a new record in 2018 (Rooney, 2019).

These robust trends in the venture-capital sector coupled with my interest in the financial markets, inspired me to study this topic in depth. I am interested in understanding how company and industry attributes influence the likelihood of venture-capital financing for firms that have gone public in recent years. The purpose of this paper is to investigate different aspects of a firm such as its debt ratio, age, industry, number of industries and whether it is a spinoff or not, to understand the effect of these attributes on the firm's choice of opting or not opting for venture-capital backing. I think this analysis is valuable because it enables firms to ascertain whether venture-capital financing is suited to them based on their characteristics and also helps venture-capitalists understand the aspects they are looking for when choosing which firms to finance.

The venture-capital space, equity markets and the intersection of the two have been widely studied over the years. In their work, Lowry, Michaely and Volkova (2017)

provide an overview of IPO literature since 2000. They analyze things such as reasons for going public, the IPO process, role of intermediaries, and post-IPO returns. This paper makes interesting points about IPO's that are venture-capital financed. Their findings indicate that venture-capital backed firms tend to be younger, more underpriced, and more likely to be in the technology industry. In their work, Gompers and Lerner attribute the increased demand of venture-capital financing to the unique value they provide firms that have uncertain futures. The recent survey of 885 VC's conducted by Gompers, Gornall, Kaplan and Strebulaev (2016) finds evidence for specific industry preferences that guide venture-capitalist decisions. Additionally, in their work, Audertsch and Lehmann (2004) test the impact the amount of debt a firm has on its likelihood of being venture-financed. A firm with a higher amount of debt is less likely to receive venture-capital backing as per their analysis.

Common themes have emerged in existing literature that have led me to study specific variables in my analysis. Therefore, I choose to focus on specific firm attributes such as age, industry, number of industries, spinoff status and debt ratios to ascertain their likelihood of being venture-financed. To do so, I run a logit regression on 280 IPO's between 2015-2019. My analysis finds that younger firms and firms in either the technology or biotechnology industry are more likely to be venture-capital backed. The debt ratio also seems to be negatively related to likelihood of being VC-financed. However, I am unable to find evidence for the relation between spinoff status and number of industries, but I attribute this deficiency to the small size of my sample.

My paper formulates hypotheses based on existing research and makes important contributions. First, it uses more recent data (2015 to 2019) which enables my analysis to capture current trends. Second, I restrict my study to the characteristics of venture-backed IPO's to firms that went public in the U.S. This eliminates the potential effect of geographical factors. Third, my analysis focusses on specific features of firms that went public (age, spinoff, number of industries, nature of industry, debt ratio) holistically. Together, these relevant factors enable me to arrive at meaningful conclusions related to what VC's look for in firms and what firms look for in their financing choices.

The remainder of this paper is organized as follows. I begin Section 2 by conducting a literature review. Having looked at existing research and the gaps this paper fills, in Section 3 I describe the data I used in my analysis. In Section 4, I explain my empirical strategy to analyze this data and the corresponding results of the analysis. Lastly, I conclude in Section 5.

2) Literature Review

Venture-backed IPO research has analyzed different aspects of the VC decision making process and firm outcomes. There have been interesting hypotheses that have emerged as a result of this research and that people have attempted to test. For instance, hypotheses such as certification, monitoring and market power have been postulated to understand the specific role that VC's play in IPO's (Chemmanur and Loutskina, 2005). Furthermore, venture-capitalist investment preferences in terms of industry, age, ownership structure, size, accounting system, and debt profiles have been subjects of study.

The tendency of younger firms to be venture-backed has been supported by existing literature. In their work, Lowry, Michaely and Volkova (2017) assert that “young age and membership in a technology industry are associated with higher information asymmetry”. VC's role in screening, monitoring and advising firms should reduce this asymmetry (Lowry, Michaely and Volkova, 2017). Lowry, Michaely and Volkova use initial returns and underpricing as metrics to explain this. Although they suggest that VC backing did decrease first day returns earlier, recent studies have shown the opposite trend. In fact, they mention research which finds IPO underpricing to be 5-10% higher in VC-backed firms as opposed to non-VC backed firms (Lowry, Michaely and Volkova). As a result, these metrics seem to be incomplete measures of VC preferences.

A lot of VC-decision making is also likely to be guided by who demands their services. Gompers and Lerner (2001) look at the kinds of firms that require the specialized services of VC's which in turn drive the kinds of firms VC's invest in. They allude to the lack of appropriate alternate financing options for young firms in specific lines of business. For instance, they say a young high-technology firm that raises equity from outside investors will be at risk of manager's making wasteful expenditures that benefit the manager and hurt the firm (Gompers and Lerner, 2001). Similarly, in the case of this firm being debt financed, a manager can make decisions that put the firm under undesirable risk. They say that this issue with alternate financing sources is further aggravated when firms have intangible assets such as heavy R&D and human capital. For instance, "entrepreneurs may invest in strategies, research, or projects that have high personal returns but low monetary payoffs" (Gompers and Lerner, 2001). Furthermore, these financing alternatives do not work because "if all the entrepreneurial outcomes of the firm cannot be foreseen, the effort of the entrepreneur cannot be ascertained with complete confidence, it may be difficult to write a contract governing the financing of the firm" (Gompers and Lerner, 2001).

Therefore, external financing options seem sub-optimal for firms with such profiles. It is these unique set of problems that specialized financial intermediaries like venture-capitalists solve by utilizing tools such as due-diligence, allocating capital based on stages, taking board seats to control or influence firm outcomes and structuring atypical compensation arrangements such as stock options (Gompers and Lerner, 2001).

The above research helps conceptualize financing decisions as a two-way model. Specific types of firms with certain types of profiles need venture-capitalist financing and at the same time venture-capitalist financing is suitable to firms with specific features and attributes. Their services are also most valuable to these firms. For instance, monitoring a well-established firm that has been doing the same type of business for decades and has a more predictable growth trajectory doesn't create as much value as doing the same for a young, uncertain firm in a high-growth industry with an uncertain trajectory.

Furthermore, research seems to support the hypothesis that VC firms are more likely to invest in firms operating within fewer industries. Gompers, Gornall, Kaplan and Strebluaev's survey of VC's finds that "62% specialize in a particular stage, 61% in a particular industry and 50% in a particular geography". In fact, 20% of VC's they surveyed indicated they specialize in the IT industry which encompasses software, IT and consumer internet. Similarly, 13% indicated they specialize in healthcare. Specialization here means VC's who stated that they only invest in these sectors and none other. This is further supported by the work of Barry (1994). He says, "a number of venture-capitalists specialize by emphasizing a particular industry, such as biotechnology" (Barry, 1994). This feature of specialization seems fundamental to the venture-capital industry as they are "assumed to have a higher technological expertise that makes it possible for them to better identify projects" (Auderstch and Lehmann, 2004).

Auderstch and Lehmann empirically test the relationship between the amount of debt a firm has to its likelihood of being venture-capital financed. They formulate two contradicting hypotheses to test this theory. Firstly, they hypothesize that "the higher the

amount of debt, the lower the likelihood that the firm will receive venture-capital” (Auderstch and Lehmann, 2004). This hypothesis is rooted in theory that debt and venture capital act as substitutes to one another. On the other hand, they hypothesize that debt and venture capital act as complements and “venture-capitalists might see the entrepreneur’s levels of debt as a quality signal and invest in the company” (Auderstch and Lehmann, 2004). To test these hypotheses, they run probit regressions on 341 firms that were listed on the German Neuer Market between 1997-2002. Their results show that the likelihood of receiving venture-capital is negatively related to the amount of debt the firm has.

Therefore, it can be seen that the role of venture-capital firms in IPO’s along with their functioning and decision-making criteria has been widely studied. A lot of work has emphasized the role of venture-capitalists in dealing with firms that tend to have informational asymmetry. This points towards the fact that young firms and firms in technology and biotechnology industries are more likely to be venture-backed. Furthermore, the intangible nature of assets of firms in these industries (technology and biotechnology) and their heavy reliance on R&D supports the hypothesis that their likelihood of being venture financed is negatively related to the amount of debt they have.

Additionally, the unique services of specialized financial intermediaries like venture-capitalists which seem to look for very specific attributes in their investee companies incline me to believe that firms operating in a fewer number of industries are more likely to be venture-backed. This is because the specific selection criteria of

venture-capitalists narrow down the scope of business. Also, while collecting data on venture-backed IPO's, I came across some firms that were spun out of larger corporations. I included these firms in my analysis and hypothesized that they would be less likely to be venture-backed. I expect that spinoffs would have access to some form of financing through their parent company which would act as a substitute and reduce the likelihood of venture-financing. This is an extension of the substitute financing hypothesis postulated by Audestch and Lehmann which suggested that firms with access to non-venture financing such as debt reduces their likelihood of being venture-backed.

3) Data

I used data recommended by Jay Ritter from the website IPOscoop which has been rating all IPO's since the year 2000. This dataset contains information about firms that have gone public since 2000 in chronological order. It contains the name of the IPO, the name of the underwriter, offer price, closing price, etc. I chose this dataset because it provided me with a reliable record of firms that have gone public in a date-organized format.

I restrict this dataset to only analyze firms that have gone public in the past 5 years, including the current year (2015-2019). I chose this constraint so that I could look closely at current trends. In my analysis, I placed restrictions on firms that have gone public within this period. First, I eliminated firms that are penny stocks wherein I define penny stocks as firms that have offer prices of \$5.00 and below (Ritter, 2018). This omitted 28 observations. Then, I excluded firms that were blank check companies, special purpose finance vehicles and REIT's. I defined blank check companies as companies "formed for the purpose of entering into a merger, share exchange, asset acquisition, stock purchase, recapitalization, reorganization or other similar business combination" (U.S Securities and Exchange Commission, 2019). This restriction led to the omission of 102 observations. Special finance vehicles are similar to blank check companies in that they have no tangible operating business but serve as mere legal entities to carry out transactions. I excluded 2 observations based on this definition of finance vehicles. A firm is a REIT (Real Estate Investment Trust) in my analysis if it either explicitly defines itself as being one in its S-1 SEC filings or if Pitchbook's database lists it as being one. I

identified 11 REIT firms in my data and dropped them. These exclusions led to a total of 144 omissions from my dataset.

After imposing these restrictions on the data, I analyzed every alternate firm in the dataset (which is arranged date-wise). I did this to maintain a random sample and ended up with 280 observations. For each of these 280 firms, the dependent variable is if it is VC-backed or not. On the other hand, the independent variables were the industry of the firm, number of industries it is in, debt ratio, age of firm, and whether it is a spinoff. The specific variable definitions that I used to maintain consistency are as follows:

Dependent Variable

VC-Backed (Yes or No): In my analysis, I used a binary variable for my dependent variable. I define a firm as being VC-Backed if on Pitchbook its financing round history section contains even one round of financing listed as a venture capital round. I also look at the Deal Type section on Pitchbook which classifies deals as PIPE, IPO, VC, etc. If any deal is listed as a VC deal, then I assigned a value of “Yes” or “1” to it in my analysis and classified the firm as being VC-backed. If there is no such round or deal classification mentioned in Pitchbook’s database, then I attributed a value of “No” or “0” to the variable.

Independent Variables

Age of Firm: I defined the age of the firm according to the year Pitchbook listed it was founded. The aim of including this variable was to confirm the hypothesis that venture-capital backed firms are likely to be younger than ones that are not venture-backed.

Spinoff (Yes or No): I looked at whether the firm is a spin off or not. This information is specifically mentioned in Pitchbook. If a firm was a spinoff then I assigned a value of “Yes” or 1 to it and if there is no such information, then I recorded it as “No” or 0. One would imagine that firms that have been spun out of other companies are less likely to be venture-capital financed since they have the option of utilizing the financial resources of their parent organization.

Industry: I classified the firms into three broad categories of industry- Technology, Biotechnology or Other. To maintain a standard and consistent method of classification, I used SIC (Standard Industrial Classification) codes. I defined a Biotechnology company as one whose nature of business corresponds to SIC codes used by Jay Ritter¹. Similarly, Technology firms are defined as those whose nature of business corresponds to the SIC codes by Jay Ritter². For firms that did not fall under the above two categories and corresponded to different SIC codes, I classified them as Other. One would imagine a larger proportion of firms in technology and biotechnology industries to be venture-capital financed.

Number of Industries: I assigned a numerical value to each firm depending on how many distinct SIC codes that corresponded to its business. For instance, a firm in a very specific

¹ SIC codes for Biotechnology: 2830 (*Drugs*), 2833 (*Medicinal Chemicals and Botanical Products*), 2834 (*Pharmaceutical Preparations*), 2835 (*In Vitro and in Vivo Diagnostic Substances*), 2836 (*Biological Products, except Diagnostic Substances*) and 8731 (*Commercial Physical and Biological Research*)

² SIC codes for Technology: 3571, 3572, 3575, 3577, 3578 (*computer hardware*), 3661, 3663, 3669 (*communications equipment*), 3823, 3825, 3826, 3827, 3829 (*measuring and controlling devices*), 3841, 3845 (*medical instruments*), 4812, 4813 (*telephone equipment*), 4899 (*communication services*), and 7370, 7371, 7372, 7373, 7374, 7375, 7378, and 7389 (*software*)

line of work would correspond to only 1 industry. On the other hand, for a conglomerate this value would be greater than 1. These codes were also explicitly listed on Pitchbook. The fact that venture-capitalists tend to specialize in specific industries would incline one to believe that firms operating in a lower number of industries are more likely to be venture-backed.

Debt Ratio: To calculate the debt ratio, I used the simple formula of *Total Liabilities / Total Assets*. I obtained the data from Pitchbook's Financials section and used the ratio for the most current fiscal year. I used the most current debt ratio because it is representative of the firm's current status of business and state of affairs. In some cases, where the data was unavailable on Pitchbook, I directly calculated the ratio from the firm's SEC S-1A filing's Consolidated Financial Statements section. Due to the nature of venture-capital financing one would expect firms with lower debt ratios to be more likely to be venture-capital backed.

4) Empirical Strategy & Results

To determine the role of VC-backing in firms depending on their age, industry, number of industries, debt ratio and spinoff status, I used the following logit equation:

$$Y_i = \beta_0 + \beta_1(Age) + \beta_2(Spinoff_j) + \beta_3(Industry_k) + \beta_4(No. of Industries) + \beta_5(Debt Ratio) + \varepsilon$$

The variable Y_i represents if a firm was VC-backed or not where i = “Yes/1” or “No/0”.

Similarly, for $Spinoff_j$, j = “Yes/1” or “No/0”. Lastly, for $Industry_k$, k =

Technology, Biotechnology or Other. The age variable is also computed in logarithmic form. Table 6 shows the results of the logit regression and the odds ratio³.

VC-Backing and Age of the Firm

The firm age values ranged from 2 years to 161 years in the sample. The summary statistics show that the mean age for a venture-backed firm is 11.71 years with a standard deviation of 10.03. On the other hand, the mean age for a non-venture-backed firm is 28.13 years, 16.42 years higher than that of a venture-backed firm. Similarly, the standard deviation is 32.11 which is 22.08 higher than that of a venture-backed firm. The results indicate sizeable differences in age between both categories of firms. The results for “Age of Firm” are statistically significant. The regression shows that younger firms are more likely to be VC-backed as can be seen by the coefficient -.04 in the regression. The odds ratio of 0.96 suggests that for each additional year of age, the likelihood of a firm

³ All variables included in this equation are defined in Section 3 (Data)

being VC-backed decreases by 0.96. However, the standard deviation of this variable indicates a skewed distribution (shown in Table 3). Therefore, I ran an alternate regression using the logarithmic value of the age variable to even out the effects of this skewed distribution. The results for “Log (Age of Firm)” are also statistically significant and have a corresponding negative coefficient and an odds ratio of 0.52. This is consistent with my hypothesis that younger firms are more likely to be VC-financed.

VC-Backing and Spinoff

The small size of the sample (280 observations) and corresponding few values for firms that are spinoffs (22 observations) resulted in no statistical significance. However, 63.63% of spinoffs in the sample were VC-backed and 36.36% were not. Spinoffs in biotechnology and technology industries such as Arlo Technologies, Magenta Therapeutics, and Autolus Therapeutics were VC-backed. On the other hand, spinoffs in other industries such as 360 Finance, Lantheus Holdings, and Studio City Holdings were not backed by venture-capital. The hypothesis of spinoffs being less likely to be VC-financed due to existing support from their parent company can be explored further with a larger dataset. Additionally, the data suggests the role of other factors such as nature of industry influencing this variable.

VC-Backing and Industry of Firm

The results for nature of industry of firm yielded statistically significant results. Biotechnology firms are more likely to be VC-financed as shown by the coefficient 3.11. The odds ratio suggests that as opposed to other industries their likelihood of being VC-financed is 22.31 times higher. This is further supported by the fact that 89.77% of biotechnology firms in the sample had received venture-capital financing and only

10.22% had not. Similarly, Technology firms are more likely to be VC-financed as shown by the coefficient 2.48. The odds ratio suggests that as opposed to other industries their likelihood of being VC-financed is 11.92 times higher. Again, 82.01% of technology firms in the sample were venture-backed as opposed to 17.91% that were not. On the other hand, out of the firms categorized as being in “Other” industries, only 25.6% had received venture-capital backing and the other 74.4% were financed via other methods. These results uphold the hypothesis that technology and biotechnology firms are more suited to VC-financing and more sought after by VC’s as opposed to firms operating in other industries.

VC-Backing and Number of Industries

Summary statistics indicate that the number of industries ranged from 1 to 4 in the sample. The mean value for number of industries for venture-backed firms was 1.37, 0.21 lower than that of non-venture-backed firms which had a mean of 1.58. Additionally, the standard deviation was 0.50 for venture-backed firms as opposed to 0.66 for firms that are not VC-backed resulting in a difference of 0.16. The regression yielded a coefficient of -0.45 suggesting that the lower the number of industries, the higher the likelihood of being VC-backed. Similarly, the odds ratio of 0.64 suggests that each additional industry reduces the likelihood of VC-financing by 36%. Although this is consistent with my hypothesis, the results were not statistically significant.

VC-Backing and Debt Ratio

The debt ratios, measured as Total Liabilities / Total Assets, ranged from 0.02 to 10.7 in the sample. Summary statistics indicate that the average debt ratio for a venture-backed firm is 0.50 with a standard deviation of 0.66. Whereas the debt ratio of a non-VC-

financed firm is 0.76 with a standard deviation of 1.01. This results in a difference of 0.26 in the average debt ratio and 0.35 in the standard deviation of debt ratios. The coefficient of -0.344 in the logit regression supports the hypothesis that lower debt ratios are more conducive to VC-financing. Furthermore, the odds ratio of 0.71 indicates that the likelihood of VC-financing reduces by 0.29 with every 1 unit increase in the debt ratio. The results support the fact that since debt is considered a cheaper alternative to equity, firms that can raise debt (have higher debt ratios) are not likely to opt for venture-capital financing. The findings are consistent with my hypothesis.

5) Conclusion

Venture-capital financing has emerged as an important financing method whose dominance is continuing to grow in the financial markets as can be seen in my analysis. A lot of existing literature has investigated venture-capitalist decision making and various venture-backed IPO metrics to gain insights into the VC-space.

My analysis of 280 firms that went public in the U.S in the years 2015-2019 indicates that technology and biotechnology firms are more likely to be VC-financed. I also discovered that the debt ratio and age of the firm bear a negative relation with the likelihood of it being financed by a VC. This is relevant in that it helps identify key metrics that drive venture-capital decisions. It is helpful to firms in that it can help them understand the method of financing best suited to them. Moreover, the study can serve as a guide to venture-capitalists and help them better define their selection criteria.

The small sample size did not yield definitive results for the relationship between venture-financing and spinoff firms as well as venture-financing and number of industries a firm operates in. I think that by analyzing IPO's over a larger time frame, future research can establish relationships between the effect of these factors on venture-backing. Additionally, there exist a lot of other important determinants such as strength of team, business model and competitive landscape that are fundamental to the way venture-capitalists make decisions. An in-depth study into these can lead to meaningful conclusions.

6) References

- Auderstch, D.B., & Lehmann, E.E. (2004). Financing High-Tech Growth: The Role of Banks and Venture Capitalists. *Schmalenbach Business Review*.
- Barry, C.B. (1994). New Directions in Research on Venture Capital Finance. *JSTOR*.
- Chemmanur, T. J., & Loutskina, E. (2006). The Role of Venture Capital Backing in Initial Public Offerings: Certification, Screening, or Market Power? *SSRN Electronic Journal*. doi:10.2139/ssrn.604882
- Gompers, P., & Lerner, J. (2001). The Venture Capital Revolution. *Journal of Economic Perspectives*, 15(2), 145-168. doi:10.1257/jep.15.2.145
- Gompers, P., Gornall, W., Kaplan, S., & Strebulaev, I. (2016). How Do Venture Capitalists Make Decisions? *NBER*. doi:10.3386/w22587
- Lowry, M., Michaely, R., & Volkova, E. (2017). Initial Public Offerings: A Synthesis of the Literature and Directions for Future Research. *SSRN*. doi:10.1561/05000000050_app
- PitchBook. (n.d.). Retrieved from <http://www.pitchbook.com/>
- Ritter, Jay (2018, June 13). Initial Public Offerings: VC-backed IPO Statistics Through 2017. Retrieved from <https://site.warrington.ufl.edu/ritter/>
- Rooney, K. (2019, January 10). Venture capital spending hits all-time high in 2018, eclipsing dotcom bubble record. Retrieved from <https://www.cnbc.com/2019/01/09/venture-capital-spending-hit-all-time-high-in-2018-eclipsing-the-dot-com-era-record.html>
- SCOOP Track Record From 2000 to Present. (n.d.). Retrieved from <https://www.iposcoop.com/scoop-track-record-from-2000-to-present/>
- Settles, P. (2019, April 11). VC Investment In The U.S. Remains Strong At \$32.6 Billion In Q1' 2019 With Unicorn IPOS Looming: KPMG Report. Retrieved from <https://www.prnewswire.com/news-releases/vc-investment-in-the-us-remains-strong-at-32-6-billion-in-q1-2019-with-unicorn-ipos-looming-kpmg-report-300830415.html>
- U.S Securities and Exchange Commission. (2017, February 05). Retrieved from <http://www.sec.gov>

Table 1) Summary Statistics

Summary Statistics of venture-backed versus non-venture-backed firms in my analysis

<u>Variable</u>	<u>VC-Backed (1)</u>	<u>Not VC-Backed (2)</u>	<u>Difference in Means (1-2)</u>
	Mean, Standard Deviation	Mean, Standard Deviation	
Debt Ratio	0.50, 0.66	0.76, 1.01	-0.26***
No. of Industries	1.37, 0.50	1.58, 0.66	-0.21***
Age of Firm	11.71, 10.03	28.13, 32.11	-16.42***

*** p<0.01, ** p<0.05, * p<0.1

Table 2) Range of Variables (Min.-Max)

Range of dependent and independent variables used in the analysis

<u>Variable</u>	<u>Range (Minimum- Maximum)</u>
VC-Backed	0 – 1
Debt Ratio	0.02 – 10.7
No. of Industries	1 – 4
Age of Firm	2 – 161 ⁴
Spinoff (Y/N)	0 – 1
Biotech	0 – 1
Technology	0 – 1
Other	0 – 1

⁴ The age variable is not normally distributed

Table 3) Distribution of Age Variable

Distribution of the age variable

<u>Age of Firm (in years)</u>	<u>Number of Firms</u>
0-25	239
25-50	21
50-75	11
75 and above	9

Table 4) Percentage Distributions

Percentage of total firms and spinoffs venture-backed versus non-venture-backed as well as firms in each industry venture-backed versus non venture-backed

<u>Variable</u>	<u>VC-Backed (%)</u>	<u>Not VC-Backed (%)</u>
IPO's	59.29	40.71
Biotech	89.77	10.22
Technology	82.01	17.91
Other	25.6	74.4
Spinoff	63.63	36.36

Table 5) OLS Regression

OLS regression results using dependent variable (VC-backed) and independent variables (age of firm, spinoff status, industry, and debt ratio) for both models (age and log(age))

VARIABLES	(1) VC-Backed	(2) VC-Backed
Age of Firm	-0.00327*** (0.00103)	
Log (Age of Firm)		-0.09038*** (0.298917)
Spinoff (Y/N)	-0.107 (0.0856)	-0.114 (0.0858)
Biotech	0.577*** (0.0566)	0.572*** (0.0574)
Technology	0.519*** (0.0584)	0.539*** (0.0575)
Debt Ratio	-0.0622** (0.0273)	-0.0558** (0.0277)
No. of Industries	-0.0671* (0.0400)	-0.0700* (0.0400)
Constant	0.492*** (0.0750)	0.656*** (0.1060)
Observations	280	280
R-squared	0.428	0.426

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6) Logit Regression

Logit regression results and odds ratios using dependent variable (VC-backed) and independent variables (age of firm, spinoff status, industry, and debt ratio) for both models with and without the log (age of firm)

VARIABLES	(1) VC-Backed	(2) Odds Ratio	(3) VC-Backed	(4) Odds Ratio
AGE OF FIRM	-0.0382*** (0.0144)	0.96		
LOG (AGE OF FIRM)			-0.6418*** (0.2280)	0.53
SPINOFF (Y/N)	-0.950 (0.673)	0.39	-0.995 (0.671)	0.37
BIOTECH	3.105*** (0.463)	22.31	3.136*** (0.462)	23.02
TECHNOLOGY	2.479*** (0.394)	11.92	2.613*** (0.395)	13.64
DEBT RATIO	-0.344* (0.178)	0.71	-0.325* (0.177)	0.72
NO. OF INDUSTRIES	-0.454 (0.303)	0.64	-0.517* (0.298)	0.60
CONSTANT	0.572 (0.519)		1.619 (0.751)	
OBSERVATIONS	280	280	280	280

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1